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# A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications

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ABSTRACT

In future electricity systems with a high share of intermittent renewable power generation, battery technologies have the potential to support power quality and security. The growing scientific literature on batteries reflects the high attention that currently rests on these technologies. This paper reviews the existing literature on lifecycle costs of batteries in stationary applications. The primary result of this review is that, despite the current high degree of variance in technological and economic battery data, a systematic assessment of the underlying uncertainty is lacking. The present paper addresses this disparity with an investigation of the impact of uncertainty in input parameters on lifecycle costs of four battery technologies across six electricity system applications. Based on input data collected from literature and via expert interviews, a probabilistic techno-economic model was built that calculates lifecycle costs and systematically addresses uncertainty in input parameters by applying a Monte Carlo simulation. The main conclusion of this paper is that the present uncertainty in cost and technical parameters of batteries exceeds by far the differences in lifecycle costs across technologies. For most electricity storage applications, the absolute differences in mean lifecycle costs across technologies are negligible compared to the uncertainty ranges of the mean lifecycle costs. Therefore, a competition still exists between the four analyzed battery technologies and so far a leading technology has yet to emerge in any of the investigated applications.



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## 1. Introduction

In order to cope with a rising electricity demand while also attempting to mitigate climate change, many governments have begun to introduce ambitious targets and incentives for the diffusion of renewable power generation technologies [1–4]. However, the non-deterministic and intermittent nature of wind and solar power generation—which are expected to contribute the majority of future renewable power generation—may entail serious challenges for the energy system [5,6]. Besides demand side management and grid expansion, energy storage technologies are promising response options due to their ability to decouple generation and load [7].

Within the field of energy storage technologies, electrochemical batteries have a potential to play an important role to pave the way towards an energy system with a high share of renewable power generation. First, due to their fast response time and scalability, battery technologies can serve both power and energy applications and thus cover a wide range of storage applications in the electricity system[1]. Second, further advantages of battery technologies are that they can be centrally located or distributed, along with their suitability for on-, off-, and weak-grid applications [8].

While much attention rests on battery technologies, uncertainty about costs and performance of battery technologies is still impeding their large-scale deployment in the electricity system [9]. Four main factors drive this uncertainty. First, multiple battery technologies in various states of maturity with highly diverging performance characteristics compete in the market. Second, a complex set of electricity storage applications exists, ranging from power quality and reliability for end-consumers to renewables integration and ancillary services on the grid level [10]. Third, scientific sources investigating costs and performance of battery technologies are often inconsistent and exhibit high variations, even for main input parameters. Lastly, complicating this inconsistency, the actual costs of a battery system do not only depend on the technology parameters but also on the specific application in which the system is used [11]. While most literature on battery technologies compares the investment and operating costs, a fair basis for comparison of technologies should factor in lifecycle costs, as lifecycle costs vary depending on the specific application.

Previous studies on storage lifecycle costs advanced the knowledge of battery costs and performance across applications. Yet, despite the present high degree of variation of input parameters in the literature—especially for immature technologies such as stationary lithium-ion and vanadium redox flow—uncertainty in input parameters has not been taken into account systematically.

In order to address this gap in the literature, the present paper investigates the impact of uncertainty in input parameters on lifecycle costs of battery technologies across electricity system applications. To this end, four battery technologies were analyzed within six stationary electricity storage applications in two steps[2]. First, based on an extensive literature review and expert interviews, battery and application input values were derived. Second, a probabilistic techno-economic model was developed that calculates lifecycle costs and systematically addresses uncertainty in input parameters by conducting a Monte Carlo simulation. Thereby, this study strives to improve the understanding of battery costs and performance for researchers, practitioners and policy makers.

The paper is structured as follows: Section 2 shortly describes battery technologies and storage applications before reviewing the literature on lifecycle costs assessments of battery technologies. Section 3 explains the methodology and data used in the lifecycle costs modeling. The obtained results are presented and discussed in Section 4. Section 5 concludes by stating possible avenues for future research while summarizing the paper's principle contributions.

## 2. Description of battery technologies and applications; review of lifecycle costs assessments

This section is comprised of two parts: A brief overview of battery technologies and their applications within the electricity system, followed by a review of previous literature on battery lifecycle costs.

### 2.1. Battery technologies and their role in the electricity system

Generally, energy can be stored thermally (e.g., hot water tank), mechanically (e.g., pumped hydro storage, compressed air energy storage or flywheels), chemically (e.g., hydrogen), electrically (e.g., supercapacitors or superconducting magnetic energy storage) or electrochemically (e.g., batteries and flow batteries). The general principle behind the mechanism of a battery is as follows: As soon as a load is connected to the cell's terminal, electrochemical reactions take place inside the cell in which electrons are set free and transferred from one electrode to another through an external electrical circuit. Depending on the required output voltage and energy capacity, single or multiple cells are connected within a series or in parallel, or both [12]. The manifold combinations of chemicals and materials used as electrodes, electrolytes or membranes span a wide spectrum of battery technologies: From lead–acid, lithium-ion, nickel–metal hydride, nickel–cadmium, zinc–air to high-temperature batteries, such as sodium–sulfur or the so-called ZEBRA battery.[3]

Flow batteries store energy externally, i.e., the storage medium and the reaction cell (cell stack) are arranged separately [13]. In general, flow batteries consist of two electrolyte solutions—which are stored in external tanks if not in use—that are pumped into the cell stack to complete the redox reactions to create electricity [14]. Flow batteries are highly flexible and can easily be tailored for diverse applications because their energy capacity can be scaled up by either augmenting the volume or the concentration of electrolytes and because their power capacity can be increased by installing additional cell stacks [14]. The materials and chemicals used in flow batteries can vary from vanadium, polysulfide–bromide, zinc–cerium, and iron–chromium to zinc–bromine.

This paper focuses specifically upon the four battery technologies—lead-acid, lithium-ion, sodium–sulfur and vanadium redox flow batteries—that are generally perceived as promising technologies with a significant potential for grid-scale electricity storage [14,15]. Moreover, these technologies are either mature (sodium–sulfur and lead–acid) or first commercial products are available (lithium-ion[4] and vanadium redox flow), and they exhibit relatively few environmental issues (in contrast to, e.g., nickel–cadmium batteries).[5]

[1] In contrast, pumped hydro, compressed air energy storage and hydrogen storage are mostly suitable for long-term storage of large energy capacities ("energy applications"), whereas flywheels, supercapacitors and superconducting magnetic energy storage are rather considered for applications with a fast release of comparatively small amounts of energy ("power applications") [19,61].

[2] We model lifecycle costs of lead-acid, lithium-ion, sodium-sulfur, and vanadium redox flow for the six applications *Utility Energy Time-shift, T&D Investment Deferral, Energy Management* (*community scale*), *Increase of Self-consumption, Area and Frequency Regulation*, and *Support of Voltage Regulation.*

[3] The Zero Emission Battery Research Activity (ZEBRA) battery is a sodium–nickel chloride based high temperature battery.

[4] While lithium-ion batteries are well established for portable devices, this technology is described as not mature for grid-scale electricity storage [9,10].

[5] Although lead can have adverse effects on the environment at high concentrations, the actual impact of lead acid batteries is typically limited due to high recovery and recycling rates [62].

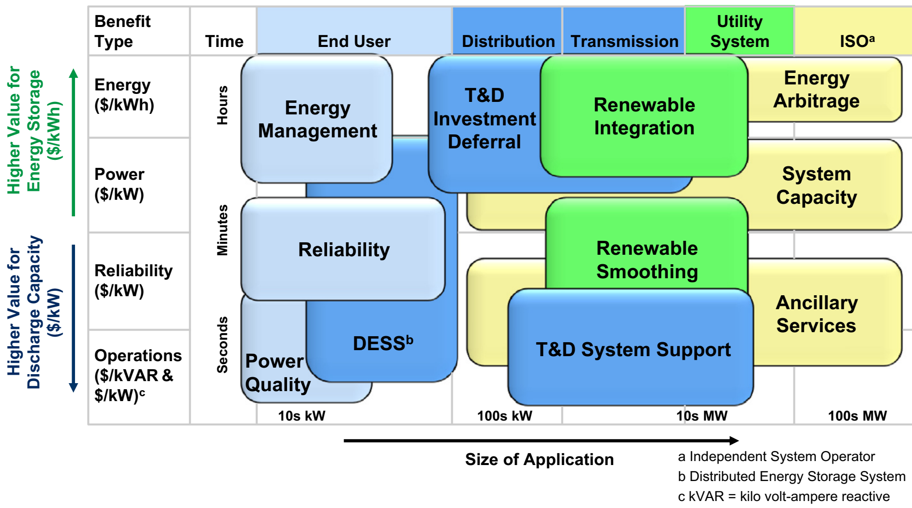



**Fig. 1.** Overview of electricity storage applications [10].

Applications that can be fulfilled by storage technologies in the electricity system are numerous and range from high power to high energy applications [16]. However, electricity storage applications are not consistently defined in the literature. Thus, both the terminology and the number of applications strongly vary across publications. As an example, a commonly used approach classifies eleven distinct applications by the size of the specific application (power rating) and the discharge duration (Fig. 1) [10]. Due to the fast response time, as well as their ability to scale energy and power rating, the four battery technologies in focus of this paper are capable of serving almost all storage applications shown in Fig. 1. Consideration must be given that, although technically feasible, the economic viability of using batteries in some applications (e.g., long-term storage of large amounts of energy) is to be questioned.

In this paper, a focus is placed upon the six electricity storage applications that are either already relevant for storage today (*Utility Energy Time-shift* and *Energy Management (community scale)*) or that will be of increasing importance with a rising share of renewable power generation (*Transmission & Distribution (T&D) Investment Deferral*, *Increase of Self-consumption*, *Area and Frequency Regulation* and *Support of Voltage Regulation*).[6]

*Utility Energy Time-shift* decouples a utility's energy generation from the energy demand on a daily basis. For instance, energy produced during off-peak hours (e.g., by base load power plants or wind parks) is stored and later discharged when energy demand is high and prices peak. *Energy Management (community scale)* shifts energy consumption over time and thus lowers the electricity costs of a community by shaving consumption peaks, by exploiting price differences in electricity tariffs or by matching actual consumption with local electricity production. *T&D Investment Deferral* responds to the challenges of the transmission and distribution grid. Due to the growing energy demand, decoupled supply and demand regions, as well the fluctuating nature of most renewable energy generation, further investment in new lines, transformers and substations may become necessary. Storage can help to defer or to avoid investments in T&D infrastructure by storing energy until there is less stress on the grid infrastructure. *Increase of Self-consumption* is an end-consumer level application. "Prosumers" (those actors who both produce and consume energy) can significantly increase the share of the produced energy (e.g., by a roof-top photovoltaic system) which is self-consumed by including storage. Higher self-consumption has two main advantages. First, it reduces the amount of energy that needs to be purchased from the energy utility, and second, it reduces the burden on the distribution grid. The primary task of *Area and Frequency Regulation* is to maintain the grid frequency at a pre-defined level by balancing short-duration differences between supply and demand. This service, also called "primary control reserve" in the European grid system, responds to an automatic control signal by the grid operator [17]. *Support of Voltage Regulation* is defined as the injection or absorption of power to support the control of reactance in the transmission and distribution grid [18].[7] In contrast to *Area and Frequency Regulation* that affects the whole grid, this ancillary service is often applied on a local level at the distribution grid.

Generally, in the storage debate, technologies and applications are classified in power (up to 30 min of discharge duration) and energy (above 30 min) [19]. Using this nomenclature, the six applications analyzed can be grouped into four energy and two power applications (*Area and Frequency Regulation* and *Support of Voltage Regulation*).

### 2.2. Lifecycle costs analyses of battery technologies

While publications and reports on storage technologies and applications are widely available, techno-economic performance has not been the focus of many publications. Often the analysis focuses on investment costs ignoring the differences in performance across applications. However, a fair comparison of technologies must rest on a lifecycle costs assessment by incorporating differences in technology lifetime, operating costs and efficiency in the calculation. In an extensive literature review, eight studies were identified that investigate lifecycle costs of storage technologies across different applications.

Table 1 lists these studies and describes the covered technologies and applications, as well as the particular input and output parameters. Additionally, it is indicated whether the particular publication provides a sensitivity analysis or investigates the impact of uncertainty in input parameters.

Comparing the absolute values of lifecycle costs across publications is difficult because the definitions of applications vary

[6] As the names of the applications are based on an exhaustive literature review, they do not have necessarily the same wording as in Fig. 1.

[7] Costs for additional components that are necessary for voltage regulation (e.g., Flexible Alternating Current Transmission Systems) are not included in the analysis.

**Table 1**
Publications on lifecycle costs analysis of battery technologies.

| Source | Author, Year | Technologies | Applications | Input parameters | Output parameter[a] | Sensitivity/ Uncertainty analysis |
|---|---|---|---|---|---|---|
| [20] | Hittinger et al. (2012) | Lithium-ion, sodium–sulfur | Frequency regulation, wind smoothing (baseload power), wind smoothing (load following), peak shaving | Based on EPRI-DOE [21] and manufacturer data | Annualized cost of energy storage [USD] | Yes/No |
| [10] | EPRI (2010) | Iron–chromium, lead–acid, lithium-ion, sodium–sulfur, vanadium redox flow, zinc–air | T&D[b] grid support, renewable integration/time shifting | Estimates based on technology monitoring efforts at EPRI | Levelized cost of electricity [USD/kWh] and levelized costs of energy capacity [USD/kW] | No/No |
| [22] | Kintner-Meyer et al. (2010) | Lithium-ion, sodium–sulfur | Balancing/ancillary services | Based on literature review (1996–2010) | Annualized cost of energy storage [USD] | Yes/No |
| [13] | Bünger et al. (2009) | NaNiCl[c], nickel–cadmium, lead–acid, lithium-ion, sodium–sulfur, vanadium redox battery, zinc–bromine | Seasonal storage, load leveling, peak shaving | Data derived from literature, reports/studies and expert interviews | Levelized cost of electricity [EUR/kWh] | Yes/No |
| [23] | Steward et al. (2009) | Nickel–cadmium, sodium–sulfur, vanadium redox flow | Energy arbitrage | Input data based on EPRI-DOE [21], Schoenung and Hassenzahl [24], Schoenung and Eyer [25] | Levelized cost of electricity [USD/kWh] | Yes/No[e] |
| [11] | Poonpun and Jewell (2008) | Lead–acid, sodium–sulfur, vanadium redox flow, VRLA[d], zinc–bromine | Generation, transmission and distribution level applications | Input data based on Schoenung and Hassenzahl [24] and manufacturer data | Levelized cost of electricity [USD/kWh] | No/No |
| [25] | Schoenung et al. (2008) | Lead–acid (flooded/VRLA[d]), lithium-ion, nickel–cadmium, sodium–sulfur, vanadium redox flow, zinc–bromine | 4 value propositions, mostly combined applications, e.g., T&D[b] deferral plus energy price arbitrage | Cost and performance data based on Schoenung and Hassenzahl [24] | Levelized costs of energy capacity [USD/kW] | No/No |
| [24] | Schoenung et al. (2003) | Lead–acid (flooded/VRLA[d]), lithium-ion, polysulfide bromide, sodium–sulfur, vanadium redox flow, zinc–bromine | Bulk energy storage (load-leveling/ load management), distributed generation (peak shaving), power quality/end-use reliability | Most data values derived from discussions with vendors/published literature | Levelized cost of electricity [USD/kWh] and levelized costs of energy capacity [USD/kW] | No/No |

[a] Original wording in publications might differ.
[b] Transmission & distribution.
[c] NaNiCl: Sodium–nickel chloride ("ZEBRA-battery").
[d] Valve-regulated lead–acid.
[e] Steward et al. supplemented their analysis of storage lifecycle costs in an energy arbitrage applications with "high costs", representing "first-generation installations and conservative estimates", and "low costs", representing "optimal of 'fully mature' technologies and many large-scale installations", estimates ([23], page 4).

across publications and because lifecycle costs depend strongly on the specific application. In the few cases in which applications are similarly defined, the resulting lifecycle costs still vary considerably.[8]

Contrarily, publications that investigate the sensitivity of lifecycle costs in relation to the changes in the input parameters mostly report consistent results in terms of these sensitivities [13,20,22,23]. Energy-related capital costs is the parameter with the highest influence on lifecycle costs, regardless of the investigated technology. In addition, operation & maintenance (O&M) costs are regularly of minor influence upon the total costs. However, some inconsistency among these publications exists in other aspects, e.g., with regards to the impact of roundtrip efficiency or electricity prices.

While these studies on storage lifecycle costs strongly improved the understanding of battery performance across applications, three potential extensions can be identified. The first and most important extension refers to the treatment of uncertainty in input parameters. The comprehensive review of battery costs and performance parameters [13,15,19,21,24–32] revealed a strong variation for almost all input values (compare Section 3.2.1). Fundamental parameters like roundtrip efficiency or calendrical life vary even for mature technologies like lead–acid or sodium–sulfur. Hence, it is pivotal to systematically account for this uncertainty in input parameters when modeling lifecycle costs in order to understand the relative competitiveness of the alternative technologies. Second, some contributions include only a very limited set of applications, often biased towards large-scale energy applications, thus disregarding power and end-consumer applications. Third, the existing literature offers room to increase the methodological rigor. With some notable exceptions [13,22,33], most publications neglect aspects such as system size optimization depending on efficiency and cycle life, and varying discount rates across applications.

## 3. Methodology and data

The following section introduces the methodology and data used in the lifecycle costs modeling. It starts with a description of the literature review and expert interviews, followed by a presentation of battery and application input data. Finally, a description of the techno-economic model is given with its three modules. Fig. 2 gives an overview of both the methodology applied and the input data used for the assessment of battery lifecycle costs.

### 3.1. Literature review and expert interviews

The input data for the techno-economic modeling of lifecycle costs was derived in two steps. First, a comprehensive literature review was conducted covering both publications in peer-reviewed journals and reports by leading research and industry

[8] For instance, while Schoenung and Hassenzahl [24] calculated lifecycle costs of lead–acid in an application with a discharge duration of six hours and 250 deep cycles per year of 0.38 USD/kWh, Poonpun and Jewell [11] estimate lifecycle costs of 0.29 USD/kWh for lead–acid in the same application.

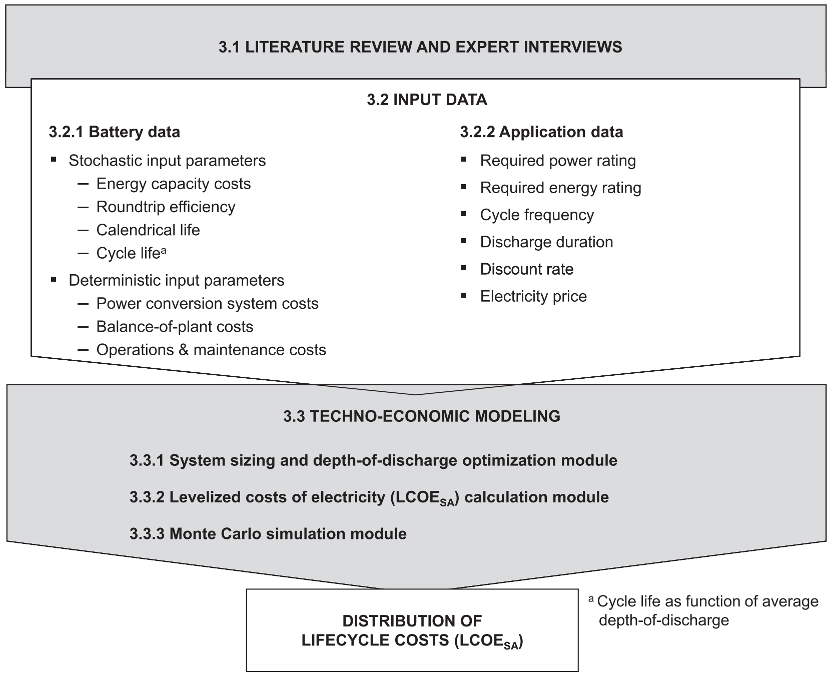



**Fig. 2.** Overview of methodology and input data for lifecycle costs modeling (including chapter numbers).

**Table 2**
Overview of participants in expert interviews.

| # | Employer | Research focus/role |
|---|---|---|
| 1 | University | Energy storage |
| 2 | University | Solid state chemistry |
| 3 | Research institute | Decentralized energy systems |
| 4 | Research institute | Energy autarky |
| 5 | Research institute | Electrochemical energy storage |
| 6 | Research institute | Electrochemistry |
| 7 | Battery manufacturer | Head of sales |
| 8 | Battery project developer | Project manager |
| 9 | System integrator | Head of battery research |
| 10 | Energy utility | Head of corporate development |

institutions. Second, the resulting data was triangulated and validated through expert interviews. In total, ten experts were interviewed between February and April of 2012. Interviewees included professors from technical universities, heads of departments of research institutes, and practitioners from energy storage companies. Each interview lasted between 30 and 60 min and was conducted either in person or via phone. Besides battery and application input data, the calculation method and the results were discussed in these interviews as well. Table 2 gives an overview of the interview participants.

## 3.2. Input data

### 3.2.1. Battery data

The modeling of lifecycle costs required a set of seven battery input parameters: Energy capacity costs, power conversion system costs, balance-of-plant costs, operation & maintenance costs, roundtrip efficiency, calendrical life and cycle life.[9] Of the aforementioned, the energy capacity costs, roundtrip efficiency, calendrical life and cycle life have the highest impact on lifecycle costs and thus were included in the Monte Carlo simulation as stochastic input parameters [34]. By depicting the variation in the literature for these four parameters across technologies, Fig. 3 highlights the uncertainty present in these parameters. The numerical values in Fig. 3 indicate the input values for the Monte Carlo simulation. In general, the required stochastic input parameters for the PERT distributions in the Monte Carlo simulation (low, mode (most likely), high) were based on the “minimum”, “mean” and “maximum” values of the literature review (compare Section 3.3.3). Furthermore, these inputs were discussed in the expert interviews, which can be summarized as follows. Literature values of battery parameters have been validated for the lithium-ion and sodium–sulfur technologies without any reservations, while values for lead–acid and vanadium redox flow were questioned in the interviews. The energy capacity costs for lead–acid, retrieved from literature, were considered too high by most experts. As a consequence, the mode in the Monte Carlo simulation for lead–acid is based on the “average lower bound” instead of the mean from the literature review.[10] The costs of vanadium redox flow were described as too optimistic. Since marketability of vanadium redox flow batteries has only recently begun with first commercial products from a few manufacturers, the data accuracy, especially with regards to costs, was questioned several times by the experts interviewed. Therefore, a more conservative approach was chosen for that technology, implementing the “average upper bound” of the literature review for the mode of the energy capacity costs in the Monte Carlo simulation.

Table 3 shows the input values derived from the literature review for the remaining deterministic battery parameters: Power conversion system costs, balance-of-plant costs and operation &

[9] When comparing battery systems of different sizes in the various applications lower costs for larger systems might be assumed due to project level economies of scale. However, small applications often have large market potentials, resulting in market level economies of scale. Therefore, battery cost input data was assumed to be equal across applications.

[10] The “average lower (upper) bound” constitutes the mean of the lower (upper) bounds of the ranges for battery parameters retrieved in the literature review.

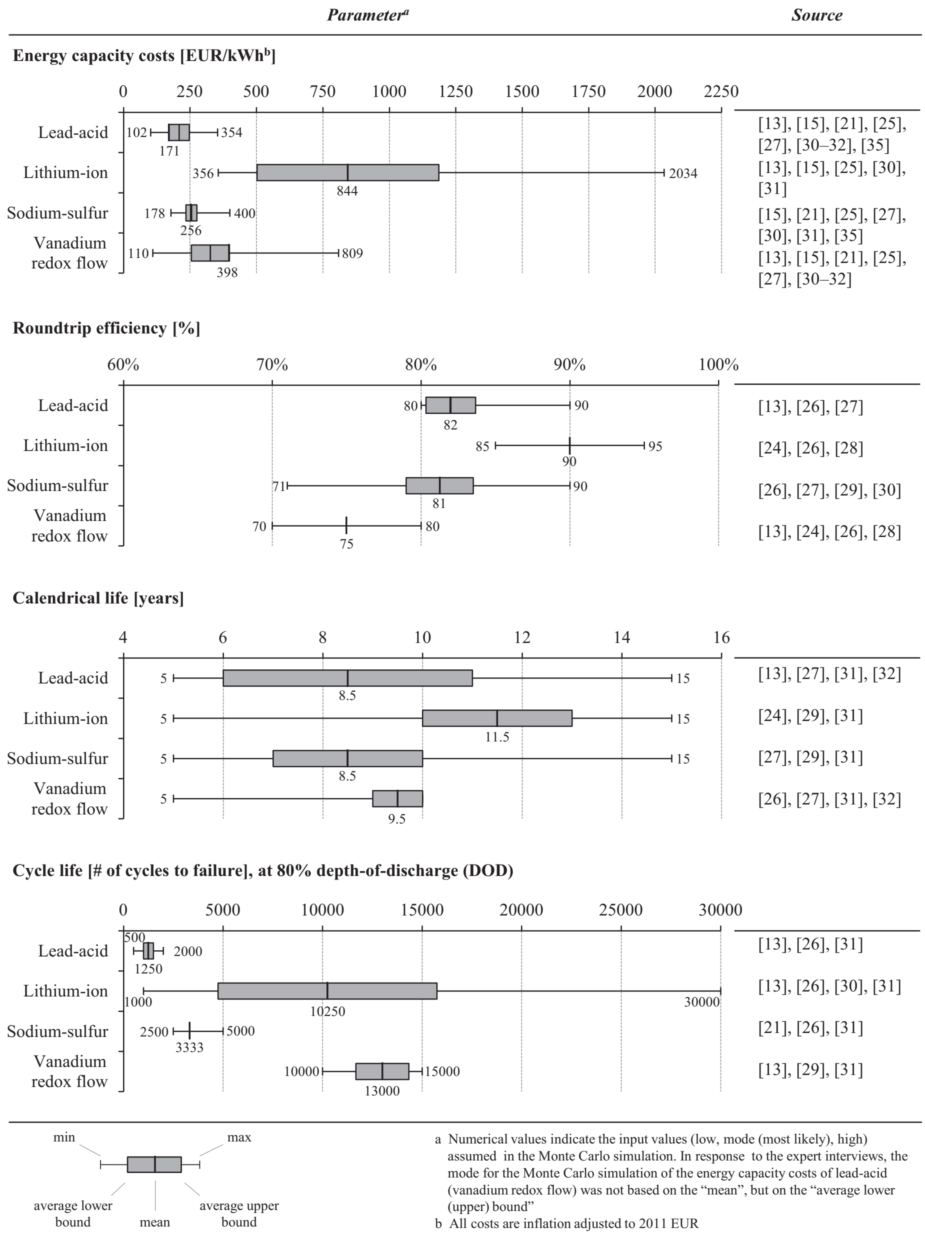



**Fig. 3.** Stochastic battery input data included in Monte Carlo simulation.

**Table 3**
Deterministic battery input data.

| *Parameter*[a] | *Unit* | *Lead–acid* | *Lithium-ion* | *Sodium–sulfur* | *Vanadium redox flow* | *Source* |
|---|---|---|---|---|---|---|
| Power conversion system costs | [EUR/kW] | 172 | 125 | 171 | 271 | [21,25,27,32,35,36] |
| Balance-of-plant costs | [EUR/kW] | 70 | 0 | 53 | 63 | [24,25,36] |
| Operation & maintenance costs | [EUR/kW p.a.] | 22 | 19 | 45 | 43 | [25,27,36] |

[a] All costs are inflation adjusted to 2011 EUR.

maintenance costs. Costs for recycling and disposal were not included in the lifecycle costs calculations, yet will be discussed in the results section (compare Section 4.1).

### 3.2.2. Application data

In general, each application can primarily be characterized by the required power rating [MW], discharge duration [h] and cycle frequency [cycles/day], i.e., the required number of cycles per day or per year. Discount rate and electricity prices are further application-specific parameters. With the exception of *Area and Frequency Regulation*, the application-specific input parameters were derived from the literature and validated in the expert interviews. The input values for these five parameters are shown in Table 4.

Generally, it is presumed that during one cycle the amount of energy [MWh], which is specified by the individual application requirements, is withdrawn from the battery system. The only exception to this rule is *Area and Frequency Regulation* where the average cycle corresponds to 38 s while the sizing of the battery

**Table 4**
Application input data.

| *Application* | *Required power rating* [MW] | *Discharge duration* [h] | *Required Energy rating* [MWh] | *Cycle frequency* [cycles/day] | *Electricity price* [EUR/MWh] | *Discount rate* [%] | *Source* |
|---|---|---|---|---|---|---|---|
| **Utility Energy Time-Shift**[a] | 100 | 8 | 800 | 1 | 50 | 8% | [13] |
| **T&D Investment Deferral** | 10 | 5 | 50 | 0.68 | 50 | 6%/8% | [38,39] |
| **Energy Management (community scale)** | 0.1 | 2.5 | 0.25 | 2 | 100 | 6% /8% | [13] |
| **Increase of Self-Consumption** | 0.0025 | 4 | 0.01 | 0.6 | 200 | 4%/8% | [15] |
| **Area and Frequency Regulation** | 2 | 0.25 | 0.5 | 34[b] | 50 | 6%/8% | [40][c] |
| **Support of Voltage Regulation** | 1 | 0.25 | 0.25 | 0.68 | 50 | 6%/8% | [41,42] |

[a] Bünger et al. [13] specified this application with up to 1000 MW.
[b] 34 small cycles per day (at 5% depth-of-discharge)
[c] Complemented with an analysis of grid frequency data (one week frequency data with a resolution of 5 seconds, retrieved from the Swiss electricity grid between 06/18/2011 and 06/24/2011)

system has to allow for a discharge duration of up to 15 min.[11] A standard discount rate of 8% is applied across applications. The impact of lower discount rates is exemplified for communities and grid operators (6%) as well as for households (4%) [37]. The assumed electricity prices range between the retail prices for private end-consumers and wholesale prices for industrial companies, grid operators and utilities.

While theoretically batteries can be scaled to serve grid-scale applications due to their modular design, currently planned and installed battery projects are at maximum within the dimensions of 20–40 MW for lead–acid, lithium-ion and flow batteries and up to 80 MW for sodium–sulfur batteries.[12] Thus, the *Utility-Energy Time Shift* application with a power rating of 100 MW is at the upper limit of current realistic battery installations.

### 3.3. Techno-economic model of battery lifecycle costs

In order to assess lifecycle costs of the battery technologies under uncertainty, a probabilistic techno-economic model was set-up, which contains three separate modules. The first module calculates the battery system size with respect to roundtrip efficiency and depth-of-discharge optimization (Section 3.3.1). The depth-of-discharge can be defined as the energy withdrawn from a battery, expressed as a percentage of the full energy capacity. Second, given the optimal system size, battery and application input data are used to calculate lifecycle costs of these technologies in terms of levelized costs of electricity for storage applications ($LCOE_{SA}$) (Section 3.3.2). Third, a Monte Carlo simulation is conducted with the main battery input parameters resulting in a distribution of lifecycle costs for each combination of the four technologies with each of the six applications (Section 3.3.3).

[11] For *Area and Frequency Regulation*, additionally to the literature review, a set of grid frequency data has been analyzed (the data is based on one week frequency data with a resolution of 5 s, retrieved from the Swiss electricity grid between 06/18/2011 and 06/24/2011). Since devices serving primary control reserve have to be available for a maximum of 15 min (European Network of Transmission System Operators for Electricity (ENTSO-E)) the discharge duration for *Area and Frequency Regulation* is set to a quarter of an hour. The analysis of the frequency data reveals an average of 34 occurrences per day, defined as the situation where grid frequency leaves the standardized frequency band of 49.95 Hz to 50.05 Hz. The mean duration of an occurrence was 38 seconds, amounting to 4.2% of the required maximum availability of 15 min. Thus, the depth-of-discharge was set to 5% for this application. The approximated cycle life at 5% DOD for the four technologies is as follows: Lead–acid: 6,378, Lithium-ion: 53,733, Sodium–sulfur: 24,505 and Vanadium redox flow: 22,730. These values were confirmed as realistic during the expert interviews.

[12] An 80 MW sodium–sulfur installation was planned, although temporally halted, by Tohoku Electric Power Co. Inc. and NGK Insulators Ltd., [63].

#### 3.3.1. System sizing and depth-of-discharge (DOD) optimization module

The model's first module adapts the battery system size depending on technical characteristics and application parameters. Two aspects are included in the calculation. First, each application requires a specific amount of energy (in Wh) to be delivered by the battery system. In order to meet the required energy capacity of the application, the sizing of the system has to account for efficiency losses during storage and discharging. Second, as the cycle life of batteries can be strongly reduced by very deep cycles, the standard maximum DOD of the battery systems is set to 80%, thus increasing the required energy capacity to be installed.

An additional DOD optimization is implemented for lead–acid and sodium–sulfur batteries because only for these mature technologies reliable data on the relation of DOD and cycle life exists. The optimal sizing of the battery system depends on the cycle frequency of the application, i.e., on how often the application is used. As the cycle life of a battery can be increased with lower average DOD [43], the DOD is "one of the most interesting parameters to play with" ([44], page 32). However, because the required energy capacity is set by the specific application, a lower DOD implies a larger battery system. Taken together, this means that the lower the DOD, the higher the upfront capital investment, yet the longer the replacement intervals. Consequently, this module detects the specific optimum of system size and DOD for each combination of technology and application.

#### 3.3.2. Levelized costs of electricity ($LCOE_{SA}$) calculation module

In order to assess lifecycle costs of batteries, the second module of the model employs the concept of levelized costs of electricity (LCOE) to compare the lifecycle costs of technologies in the different applications. In general, the LCOE concept determines the total costs that occur during the lifetime of a technology divided by the lifetime energy production and thus accounts for the differences in lifetimes across technologies [45]. This methodology is often used in literature as a benchmarking or ranking tool to calculate the cost-effectiveness of different energy generation technologies and is based on the following formula [46,47]:

$$\mathrm{LCOE} = \frac{\sum_{n=0}^{N} (\mathrm{CAPEX} + \mathrm{OPEX}/(1+i)^n)}{\sum_{n=0}^{N} (kWh_{\mathrm{initial,net}}/(1+i)^n)} \quad (1)$$

where CAPEX: Investment costs [EUR]; OPEX: Operation and maintenance costs [EUR]; $kWh_{initial,net}$: Initial net electricity production [kWh]; $i$: Discount rate [%]; $N$: Plant lifetime [years].

The approach of the "Levelized Cost of Electricity for Storage Applications" ($LCOE_{SA}$) adapts the LCOE concept to storage technologies. The $LCOE_{SA}$ are defined as the total annualized costs of

the energy storage system divided by the annual energy output [23]. Importantly, the $LCOE_{SA}$ for one technology may vary strongly depending on the application. For instance, because the annual energy output enters the $LCOE_{SA}$ formula in the denominator, an application with a high energy throughput (e.g., *Utility Energy Time-shift*) is likely to have lower $LCOE_{SA}$ than an application with very little energy throughput (e.g., *Area and Frequency Regulation*). Taken together, the $LCOE_{SA}$ concept provides a useful metric to compare the costs of technologies across applications on a fair basis [10].

#### 3.3.3. Monte Carlo simulation module

As a purely deterministic $LCOE_{SA}$ calculation would neglect the strong variance in input parameters (compare Section 3.2.1), the third module applies a Monte Carlo simulation in order to assess this impact of uncertainty. In general, the Monte Carlo method is a "statistical numerical method used for solving mathematical problems" ([48], page 648) by repeatedly drawing input values for a deterministic calculation from distributions of stochastic input parameters. The calculation is conducted with each set of input parameters and the resulting output values are observed [45]. Based on the law of large numbers, the distribution of the observed output values in the Monte Carlo simulation converges to their theoretical distribution. This represents a practical approach to investigate the effect of uncertainty in case an analytic solution of the calculation is not possible or too complex.

A Monte Carlo simulation requires a distribution and the corresponding distributional parameters for each stochastic input value. A PERT distribution was assumed for the stochastic input parameters because this distribution is explicitly recommended to be used to model expert estimates as it is less sensitive to extreme values, for instance in comparison to the triangular distribution [49,50]. The PERT distribution is based on the beta distribution and was developed for the "Program Evaluation and Review Technique" analysis. In general, the "minimum", "mean" and "maximum" values from the literature review were assigned to the three input values (low, mode (most likely), high) of the PERT distribution [51]. In case this assignment was questioned within the expert interviews, the mode of the PERT distribution was based on the "average lower bound" or "average upper bound" from the literature review (compare Section 3.2.1).

For the four technologies and six applications in focus, the Monte Carlo simulations were conducted with 10,000 runs with the four stochastic input parameters: Energy capacity costs, round-trip efficiency, calendrical life and cycle life.[13] Additional Monte Carlo simulations were conducted in order to assess the impact of depth-of-discharge optimization and varying discount rates. Therefore, with a total of 540,000 simulated data points, the model is able to estimate the $LCOE_{SA}$ distributions for all technologies across applications including sensitivities to discount rate reduction and depth-of-discharge optimization.

## 4. Results

The results generated by the probabilistic lifecycle costs model are summarized in Fig. 4, in which the mean levelized costs of electricity ($LCOE_{SA}$), the impact of uncertainty in input parameters, the sensitivities to discount rate reduction and to depth-of-discharge optimization are shown.

The numerical values on the left and the length of the bars both represent the mean $LCOE_{SA}$. The impact of uncertainty in input parameters is shown by the 95% error bars, indicating the range in which 95% of the $LCOE_{SA}$ values generated by the Monte Carlo simulation lie. Sensitivities to lower discount rates (for end-consumer and community/grid operator applications) and depth-of-discharge optimization (for lead–acid and sodium sulfur) are shown by the shaded areas within the colored bars and by the green triangles respectively.[14]

Comparing the $LCOE_{SA}$ estimates in Fig. 4 with the ones from preceding studies on battery lifecycle costs requires similarly defined applications. The *Utility Energy Time-shift* application is roughly comparable with *Energy Arbitrage* in Steward et al. (2009) [23], with the *Generation* (8 *h discharge duration*) application in Poonpun and Jewell (2008) [11] and also with *Bulk Energy Storage* in Schoenung and Hassenzahl [24]. These publications are in line with our finding that sodium–sulfur has the lowest mean $LCOE_{SA}$ in this application, followed by lead–acid and vanadium redox flow in close competition. Yet deviation occurs concerning the absolute level of $LCOE_{SA}$. While our analysis confirms the $LCOE_{SA}$ value for sodium–sulfur (0.18 EUR/kWh) of Steward et al., it is higher than the estimate of Poonpun and Jewell (0.14 EUR/kWh). The result of Schoenung and Hassenzahl for sodium-sulfur in *Bulk Energy Storage* is 0.37 EUR/kWh, which is considerably higher than all other publications. However, given the earlier publication date, this might be due to technological advances within the recent years.[15]

Two steps are taken to further discuss and analyze the results. First, the absolute values and the variation of mean $LCOE_{SA}$ across applications and technologies are discussed. Second, attention is focused on the impact of uncertainty in input parameters by reviewing the distribution of $LCOE_{SA}$ in terms of 95% error bars.

### 4.1. Discussion of mean $LCOE_{SA}$ results

First, stationary battery technologies are still expensive. Contrasted with the average European electricity wholesale price (0.044 EUR/kWh) [52] and retail price (0.172 EUR/kWh) [53], battery energy storage would add considerable additional costs on the wholesale and retail level.[16] For instance, although sodium–sulfur has with 0.18 EUR/kWh the lowest mean $LCOE_{SA}$ in the *Utility Energy Time-shift* application, its costs are still substantially higher than the costs of pumped hydro which range from approximately 0.05 EUR/kWh [13] to 0.10 EUR/kWh [23] in a comparable application.

Second, mean lifecycle costs of stationary battery technologies vary strongly across technologies and applications. On the one hand, given a certain application, the mean $LCOE_{SA}$ vary strongly across technologies. For instance, for *Area and Frequency Regulation*, the mean $LCOE_{SA}$ for lead–acid (2.10 EUR/kWh) are almost three times as high as that the mean $LCOE_{SA}$ for lithium-ion (0.80 EUR/kWh). The main drivers behind this variation are the differences in investment costs and cycle life across technologies. On the other hand, given a certain technology, the mean $LCOE_{SA}$ differ to a considerable extent across applications. As a rule, the $LCOE_{SA}$ decrease with a higher utilization of the battery. Therefore, the higher the average energy throughput the lower the $LCOE_{SA}$. As a result, the mean $LCOE_{SA}$ for energy applications are lower than for power applications.

[13] The four stochastic input parameters were assumed to be mutually uncorrelated.

[14] No sensitivity to DOD optimization is shown in Fig. 4 in case the optimal DOD corresponds to the standard DOD at 80%.

[15] All cost estimates were converted to EUR and adjusted for inflation based on the year of publication.

[16] Wholesale electricity prices correspond to the average EEX spot price 2010. Retail electricity prices correspond to the unweighted average of EU-27 retail (end-user) electricity prices of May 2012.

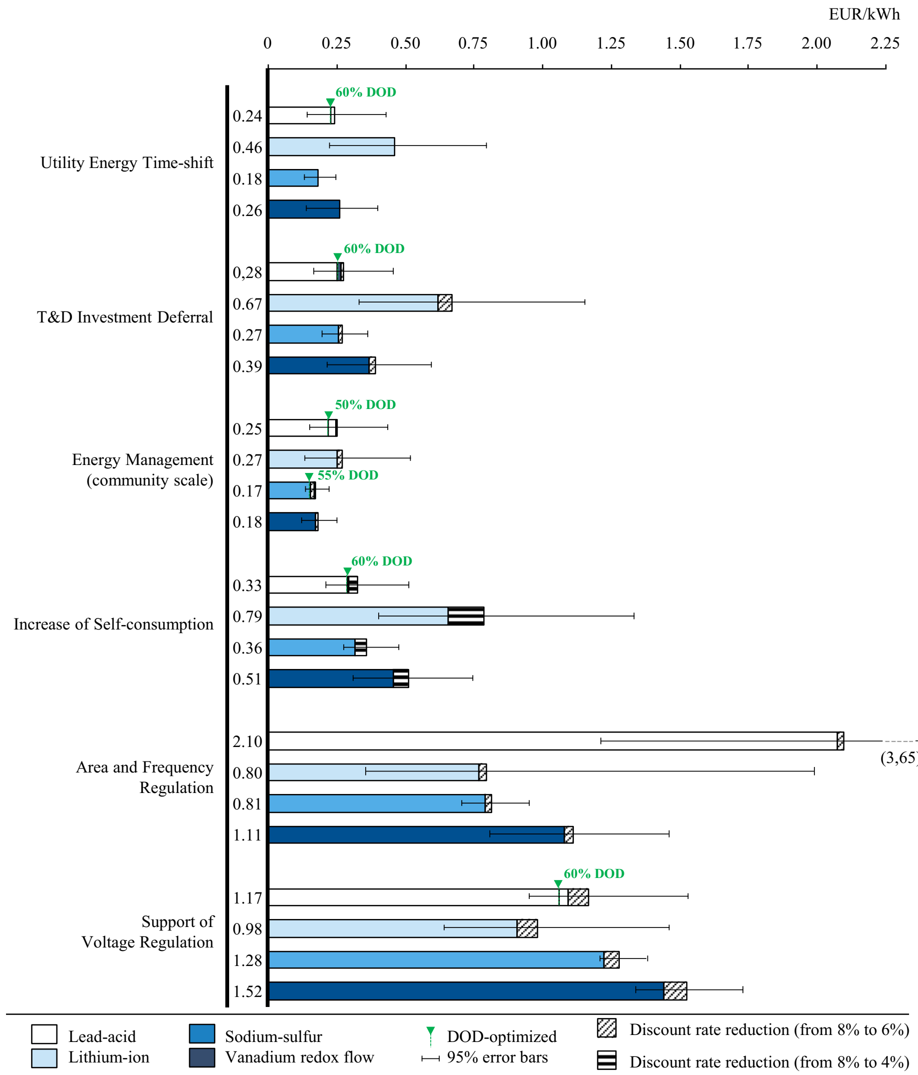



**Fig. 4.** Lifecycle costs ($LCOE_{SA}$) by application and technology.

Third, the ranking of battery technologies differs across applications. As indicated in Fig. 4, sodium–sulfur has the lowest mean $LCOE_{SA}$ in *Utility Energy Time-shift, T&D Investment Deferral* and *Energy Management (community scale)*, while lithium-ion leads in the power applications *Area and Frequency Regulation* and *Support of Voltage Regulation* and lead–acid is the most cost efficient in the end-consumer application *Increase of Self-consumption*. In general, the ranking of technologies is determined by the relative investment costs and replacement intervals, which mainly depend, in turn, on the application parameters discharge duration and cycle frequency. Hence, given low investment costs along with a short cycle life, lead–acid has a comparative advantage for small scale, yet rarely used applications. With an increasing scale and use of applications, the advantage shifts to sodium–sulfur, and with ever increasing cycle frequency, this would further shift to vanadium redox flow. Lithium-ion leads for all applications with a high power-to-energy ratio and high cycle frequency. Cost for recycling and disposal were not included in the lifecycle costs calculations. Quantitative estimates on their impact on the lifecycle costs of the four technologies are rare. Yet it seems likely that the incorporation of recycling and disposal costs would slightly benefit lithium-ion and lead-acid. For these two technologies, several studies estimate that owners might generate a small revenue from selling batteries at the end-of-life due to the value of the material included in the old battery, especially for large-scale installations [21,54–56]. In case of vanadium redox flow, a high stability of the vanadium electrolyte and a simple recycling process is likely to result in small disposal costs [15,21,57]. Sodium–sulfur batteries are describes as almost entirely recyclable (98–100%) yielding high-purity raw materials, yet no estimates on costs are available [21,58,59].

Fourth, battery lifecycle costs can be decreased by system size optimization (depth-of-discharge optimization) and by lower discount rates. First, as described in Section 3.3.1, each battery technology has a specific functional relation between the average depth-of-discharge and the cycle life. Optimizing the system size of a battery system can exploit this relationship and reduce the resulting $LCOE_{SA}$. For instance, in the *Energy Management (community scale)* application the system size optimization for the sodium–sulfur technology results in an optimal depth-of-discharge of 55%, lowering the mean $LCOE_{SA}$ by around 9%. Second, the lifecycle costs are sensitive to the discount rate. For example, in the end-consumer application *Increase of Self-consumption*, a four percentage point lower discount rate that can be assumed for households lowers the mean $LCOE_{SA}$ of lithium-ion by more than 16%.

### 4.2. Discussion of the impact of uncertainty in input parameters

First, the impact of uncertainty in battery input parameters is very high, with the 95% error bars ranging on average from 65% to

153% of mean $LCOE_{SA}$. Calculating the variation coefficient, a measure that normalizes the variation by dividing the standard deviation by the mean, results in an average value of 23%. Thus, the strong variation in the literature on battery input parameters translates into very large uncertainty ranges in the lifecycle costs of battery systems across applications. Moreover, all $LCOE_{SA}$ distributions are positively skewed, i.e., the density of the $LCOE_{SA}$ distributions is higher on the left side, while the right tail is longer. Thus, $LCOE_{SA}$ outliers tend to be on the high cost side.

Second, incorporating uncertainty in input parameters reveals that in none of the analyzed applications a clearly leading technology exists. The absolute difference in mean $LCOE_{SA}$ across technologies is often negligible compared to the error bars indicating the 95% confidence interval of the mean $LCOE_{SA}$. For instance, the error bar for lithium-ion in *Energy Management (community scale)* ranges from 49% (2.5 percentile at 0.13 EUR/kWh) to 194% (97.5 percentile at 0.52 EUR/kWh) of the mean $LCOE_{SA}$ (0.27 EUR/kWh), while the difference in the mean $LCOE_{SA}$ between lithium-ion and lead–acid is just 7%. As a result, in all six investigated applications, the error bar of the by mean $LCOE_{SA}$ cheapest technology is overlapping with the error bars of all other three technologies. The likelihood that the by mean $LCOE_{SA}$ cheapest technology is outperformed by one of the other three technologies is above 10% for all applications and reveals that for all applications a significantly leading technology does not exist. Hence, the impact of uncertainty in input parameters outweighs the differences in the mean lifecycle costs across technologies underlining the relevance of an uncertainty analysis.

Third, lithium-ion exhibits the highest uncertainty in $LCOE_{SA}$, while sodium–sulfur $LCOE_{SA}$ are the least uncertain. The Monte Carlo simulation shows that the impact of uncertainty is the highest for lithium-ion, followed by vanadium redox flow and lead–acid, while lifecycle costs of sodium–sulfur exhibit the least variation. The average $LCOE_{SA}$ variation coefficient of lithium-ion is at 36%, yet only at 12% for sodium–sulfur. These results are consistent with the fact that stationary lithium-ion is an immature technology with many different competing designs, while sodium–sulfur is an established technology produced only by a few firms worldwide. With many different producers (lead–acid) and with only a few sources reporting cost estimates (vanadium redox flow), the middle positions of the remaining two technologies are also in line with expectations.

Fourth, lifecycle costs in the *Support of Voltage Regulation* application are the least affected by uncertainty in input parameters. The average variation coefficient across technologies is at 11% for *Support of Voltage Regulation*, whereas the other five applications have variation coefficients ranging from 23% (*Increase of Self-consumption*), over 25% (*T&D Investment Deferral* and *Energy Management (community scale)*) to 27% (*Utility Energy Time-shift* and *Area and Frequency Regulation*). The reason for the relatively lower uncertainty of lifecycle costs in *Support of Voltage Regulation* is that the $LCOE_{SA}$ in this application are less sensitive to the four stochastic input parameters compared to the $LCOE_{SA}$ in the remaining five applications.

## 5. Conclusion

The present paper aims to serve as decision-making support for researchers, practitioners and policy makers by reviewing costs and performance of battery technologies while explicitly taking the uncertainty in input parameters into account.

The main result of this paper is that the present uncertainty in input parameters for batteries exceeds by far the differences in lifecycle costs across technologies. For most electricity storage applications, the absolute differences in mean lifecycle costs across technologies are negligible compared to the uncertainty ranges of lifecycle costs. Although sodium–sulfur, lead–acid and lithium-ion each exhibit cost leadership by mean lifecycle costs for specific applications, the respective relative advantage is not significant. Therefore, a competition still exists between the four analyzed battery technologies and so far a leading technology has yet to emerge in any of the investigated applications.

From our analysis, the following four points emerge as important topics for further research. First, the calculation method could be expanded to incorporate additional technical complexities. A non-linear cost structure including fixed costs and economies of scale, along with the impact of the ambient temperature on lifetime and performance, and degradation of roundtrip efficiency are just some examples. Second, in this paper a static review was conducted and focused on costs and performance factors. Potential extensions may include forecasts of future costs and performance developments or extend the assessment to additional factors, such as environmental impact or resource availability. Third, an analysis of the profitability of stationary battery systems based on the economic benefits of these applications and market potential should be conducted. Private investment in storage projects and diffusion support by policy makers require a more complete picture of storage applications by bringing together both the costs and the benefits. Fourth, future research should investigate the impact of deployment policies on firm activity in the battery industry building upon lessons learned, for instance, within the electricity sector [60].

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